# LSP Based Comparison of 3D Ear Models

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***Abstract*—Ear biometric authentication is considered to be an important aspect of human identification and is, among other techniques, used in victim identification for practical reasons . State-of-the-art techniques transform 2D ear photos to 3D ear models to adequately cope with geometrical and photometric normalisation issues. From each 3D ear model a feature list is extracted and used in the comparison process. In this paper we study how automated comparison of 3D ear models can be improved by soft computing techniques. More specifically we investigate and illustrate how multiple-criteria decision support techniques, which are based on fuzzy set theory, can be used for fine-tuning the ear comparison process. Point-to-point matching schemes are enriched with Logic Scoring of Preference (LSP) multiple-criteria decision support facilities. In this way valuable knowledge of forensic experts on ear identification aspects can be incorporated in the comparison process. The benefits and added value of the approach are discussed and demonstrated by an illustrative example.**

## I. INTRODUCTION

Ear biometrics are considered to be a reliable source for disaster victim identification. Indeed, ears are relatively immune to variation due to ageing [8] and the external ear anatomy constitutes unique characteristic features [14]. Moreover, ears are often among the intact parts of found bodies, automated comparison of photographs is in general faster and cheaper than DNA analysis and collecting antemortem photographs is considered to be a humane process for relatives.

Although there is currently no hard evidence that ears are unique, there is neither evidence that they are not. Experiments comparing over ten thousand ears revealed that no two ears were indistinguishable [4], [14] and another study revealed that fraternal and identical twins have a similar but still clearly distinguishable ear structure. More research is needed to examine the validity of uniqueness but, despite of that, an identity match or mismatch based on ear biometrics can provide forensic experts with useful information in identification tasks. This makes research on the comparison of ear photographs relevant and interesting.

When considering a missing person and the found body of a victim, ear identification practically boils down to a comparison of a set of ear photographs of the missing person on the one hand and a set of ear photographs of the victim on the other hand. Ear pictures of a victim are taken in postmortem conditions and hence referred to as postmortem (PM) pictures. Pictures of a missing person are always taken antemortem and therefore called antemortem (AM) pictures. PM pictures are assumed to be of good quality because they are usually taken by forensic experts under controlled conditions: high resolution, correct angle, uniform lighting, with the ear completely exposed. AM photos are often of lower, unprofessional quality. They are not taken with the purpose of ear identification and are usually provided by relatives or social media. Because we have no control over the conditions in which these pictures were taken, we can only hope to retrieve the best we can. Moreover, parts of the ear might be obscured by hair, headgear or other objects. The ear can also be deformed by glasses, earrings or piercings. Efficiently coping with different picture parts which are of different importance or relevancy is a research challenge and the subject of this work.

A considerable part of related work focuses on comparisons in which an ear photo originating from a given set of photos is compared to all photos in this set (e.g, [13], [20], [25]). This is a simplified case because matches between identical photos are searched for. The work in this paper is more general because it involves the matching of identical ears on different photos. An important step of each automated ear comparison process is the ear recognition step during which corresponding extracted features from two ears are compared in order to decide whether the ears match or not. Related work on ear recognition can be categorised based on the feature extraction scheme used. Intensity based methods use techniques like principal component analysis, independent component analysis and linear discriminant analysis for the comparison (e.g., [21], [22], [26]). Other categories of methods are based on force field transformations (e.g., [3]), 2D ear curves geometry (e.g., [7]), Fourier descriptors [1], wavelet transformation (e.g., [12]), Gabor filters (e.g., [17]) or scale-invariant feature transformation (e.g., [16]). A last category of comparison techniques are based on 3D shape features. Most approaches use an iterative closest point algorithm for ear recognition (e.g., [5], [6], [15], [23]). In [24] both point-to-point and point-to-surface matching schemes are used, whereas the method in [19] is based on the extraction and comparison of a compact biometric signature. An elaborate survey on ear recognition is [2].

Only a few of the approaches for ear recognition (see, e.g., [13], [20]) allow to subdivide ear photos in several parts. These parts are then compared in a pairwise fashion, after which the comparison results are aggregated. This is an

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interesting feature because parts which are not trusted can be excluded from the comparison process. This idea can be further exploited in order to incorporate forensic expert knowledge. For example, it is generally known that ears are relatively immune to variation due to ageing [8]. This holds true for the full ear shape, with the exception of the ear lobe which is known to elongate for elderly people. So, when the PM pictures are of an aged person and the AM pictures are of a person who is much younger, a mismatch of the ear lobe shape should not have a significant impact on the overall ear comparison result. Likewise, some kinds of (parts of) ear shapes are known to be extremely rare. A match for such parts should give a significant indication that the full ear shapes should match too.

In this paper we study how expert knowledge about ear comparison issues can be adequately modelled and incorporated in an ear identification method. We use a 3D ear model on which we apply point-to-point matching schemes. Traditionally, a kind of distance between corresponding points of two feature lists is computed. This distance acts as a similarity measure for the two ears represented by the two feature lists. Instead of handling all points of the feature lists at once for the computation of the similarity, we propose to consider subsets of such points, taken from specific areas of the ear shape. The comparison process is then improved based on the Logic Scoring of Preference (LSP) [11] multiple-criteria decision support technique. First, we study how similarities between two corresponding subsets of points (corresponding to a specific part of the external ear) can be measured and how this measurement can be approached as a criterion evaluation technique. Second, we describe how LSP aggregation structures can be used for combining criterion evaluations. Extra criteria for available metadata can also be integrated.

The remainder of the paper is structured as follows. In Section II some preliminaries are given. Some general issues on ear comparison are explained. Next, some basic concepts of LSP are described. In Section III, the 3D ear model is described. Section IV deals with the integration of LSP in ear recognition and comprises the main contribution of the paper. It describes how corresponding points in two 3D ear models can be compared and proposes a novel similarity measuring technique based on LSP. The benefits and added value of the approach are discussed and demonstrated by an illustrative example in Section V. Finally, some conclusions are reported in Section VI.

## II. Preliminaries

### A. General Issues on Ear Comparison

Victim identification by ear biometrics can be seen as a pattern recognition process where PM ear photos of a victim are reduced to a set of features that is subsequently compared with each of the feature sets that are obtained from the AM photos of missing persons in order to help determine the identity of the victim on the basis of the best match. The following steps are hereby distinguished:

1) *Ear detection.* Hereby, ears are positioned and extracted from the photos.
2) *Ear normalisation and enhancement.* Detected ears are transformed to a consistent ear model using, e.g., geometrical and photometric corrections.
3) *Feature extraction.* Representative features are extracted from the ear model.
4) *Ear recognition.* Feature sets of AM and PM ears are compared. A matching score indicating the similarity between the ears is computed.
5) *Decision.* The matching scores are ranked and used to render an answer that supports forensic experts in their decision making.

Errors in the first three steps can undermine the utility of the process. So, features that are obtained from bad quality data should be handled with care and forensic expert knowledge on ear comparison should be reflected as adequate as possible. For that reason, we consider that a feature set can be subdivided in subsets to which different importances can be assigned in the comparison process. Corresponding feature subsets of PM and AM ear photos are then evaluated separately and their resulting matching scores are aggregated in accordance with preferences of forensic experts that are determined beforehand.

### B. Logic Scoring of Preference

Logic Scoring of Preference (LSP) is a decision support technique that is based on the following main steps [11]. First, an attribute tree is constructed. Each attribute in the tree represents a parameter which is relevant for the decision that has to be taken. Leaf nodes correspond to elementary parameters, whereas internal nodes represent composed parameters. Next, for each elementary parameter, an elementary criterion is specified. This criterion expresses the user's preferences related to the acceptable values of the parameter. Then, for each competitive option, the elementary criteria are evaluated. By doing so, for each option, an elementary degree of suitability is obtained for each elementary parameter. Finally, these elementary degrees are aggregated in order to obtain an overall degree of suitability for each option.

Aggregation in LSP is done by using an aggregation structure. This structure is specifically designed for the decision process under consideration and has to reflect the human decision making process as adequate as possible. Among others this implies that the aggregation structure should reflect the semantics of the attribute tree. The basic components of the aggregation structure are the simple LSP aggregators, which act as logical connectives. Simple LSP aggregators can in turn be combined into compound aggregators.

The formal basis for LSP aggregators is the so-called generalised conjunction/disjunction (GCD) function which can be expressed by

$$M(x_1,\dots,x_n;w_1,\dots,w_n;r) = \begin{cases} (\sum_{i=1}^n w_i x_i^r)^{1/r} & \text{, if } 0<|r|<+\infty \\ \prod_{i=1}^n x_i^{w_i} & \text{, if } r=0 \\ x_1 \wedge \dots \wedge x_n & \text{, if } r=-\infty \\ x_1 \vee \dots \vee x_n & \text{, if } r=+\infty \end{cases} \quad (1)$$

where the values $x_i \in [0,1]$, $1 \leq i \leq n$ are the input preferences (hereby, 0 and 1 respectively denote 'not preferred at all' and 'fully preferred'); the given (or precomputed) weights $w_i$, $1 \leq i \leq n$ determine the relative importance of input preferences; and the computed exponent $r \in [-\infty, +\infty]$ determines the logic properties of the aggregator. Special cases of exponent values are: $+\infty$ corresponding to full disjunction, $-\infty$ corresponding to full conjunction, and 1 corresponding to weighted average. The other exponent values allow to model other aggregators, ranging continuously from full conjunction to full disjunction and can be computed from a desired value of orness ($\omega$), i.e., an index expressing how 'close' the aggregator should be in its behaviour to the regular disjunction operator. The following numeric approximation for $r$ can be used [11]:

$$r = \frac{0.25 + 1.89425x + 1.7044x^2 + 1.47532x^3 - 1.42532x^4}{\omega(1-\omega)} \tag{2}$$

where

$$x = \omega - 1/2 \text{ and } 0 < \omega < 1.$$

The andness ($\alpha$) is obtained as the complement of the orness, i.e.,

$$\alpha = 1 - \omega.$$

Andness is hence an index expressing how 'close' the aggregator should be in its behaviour to the regular conjunction operator.

For $\omega > 0.5$ we have disjunction. When $\omega = 1$ this corresponds with $r = +\infty$ and is called full disjunction (D). For $0.75 < \omega < 1$ a hard partial disjunction (HPD) operator is obtained, whereas $0.5 < \omega < 0.75$ yields a soft partial disjunction (SPD) operator. So, $\omega = 0.75$ can be considered as corresponding with a neutral partial disjunction operator (PD). Likewise, for $\alpha > 0.5$ we have conjunction, $\alpha = 1$ corresponds with $r = -\infty$ and is called full conjunction (C). For $0.75 < \alpha < 1$ a hard partial conjunction (HPC) operator is obtained, whereas $0.5 < \alpha < 0.75$ yields a soft partial conjunction (SPC) operator. The andness $\alpha = 0.75$ can be considered as corresponding with a neutral partial conjunction operator (PC). If $\alpha = \omega = 0.5$ the neutral (weighted) arithmetic mean operator (A) is obtained. This corresponds with the case where $r = 1$.

Two examples of compound LSP aggregators are the conjunctive partial absorption $\trianglerighteq$ (CPA) and the disjunctive partial absorption $\bar{\triangleright}$ (DPA) [9]. Both CPA and DPA have two inputs $x$ and $y$.

The CPA $\trianglerighteq$ aggregates a mandatory input $x$ and a non-mandatory (desired or optional) input $y$, as follows:

$$x \trianglerighteq y = w_2 x \Delta (1-w_2)[w_1 x \nabla (1-w_1) y] \tag{3}$$

where $\Delta \in \{C, HPC\}$ and $\nabla \in \{D, SPD, HPD, A\}$.

The DPA $\bar{\triangleright}$ aggregates a sufficient input $x$ and a non-sufficient (desired or optional) input $y$, as follows:

$$x \bar{\triangleright} y = w_2 x \nabla (1-w_2)[w_1 x \Delta (1-w_1) y] \tag{4}$$

where $\nabla \in \{D, HPD\}$ and $\Delta \in \{C, SPC, HPC, A\}$.

In both equations Eq. (3) and (4), the weights $w_1$ and $w_2$ are computed so as to reflect as adequate as possible the impact of the mean penalty $P$ and mean reward $R$ percentages provided by the user. Hereby the underlying semantics of $P$ and $R$ are defined by the following border conditions for the CPA $\trianglerighteq$ [10] (and their dual counterparts for the DPA $\bar{\triangleright}$):

$$\forall\, 0 < x \leq 1 : x \trianglerighteq 0 = x(1-p), 0 \leq p < 1 \tag{5}$$

(hence if the optional condition is not satisfied at all, then criterion satisfaction is decreased with a penalty of $p$)

$$\forall\, 0 < x < 1 : x \trianglerighteq 1 = x(1+r), 0 \leq r < 1/x - 1 \tag{6}$$

(hence if the optional condition is fully satisfied, then criterion satisfaction is increased with a reward of $r$). Note that $p$ and $r$ can be zero. The values $P$ and $R$ are (approximately) the mean values of $p$ and $r$ and are usually expressed as percentages. Users select desired values of $P$ and $R$, which are then used to compute the corresponding weights $w_1$ and $w_2$. More details on this computation can be found in [10].

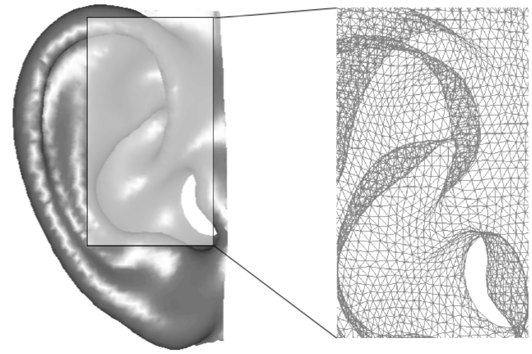

Fig. 1. 3D ear model.

## III. 3D Ear Model

In our previous work, we used 2D ear images for accomplishing ear recognition [18]. Imperfect geometrical and photometric transformations of 2D AM photos put a limit on the quality of the results. To improve this approach we now use a 3D ear model. This 3D ear model is obtained by estimating the parameters of a mathematical shape function such that the resulting shape optimally fits the images of the ear. For a PM ear, a 3D camera image can be used, whereas for an AM ear usually a set of 2D photos is used. The description of this fitting process is outside the scope of this paper. At this point it is sufficient to assume that for each ear we obtained a 3D model that captures the three dimensional details of the ear surface as shown in Fig. 1.

The 3D ear model is normalised for all ears, so all ear models have the same resolution and scale and can be compared without having to deal with scaling and orientation issues.

Feature extraction boils down to selecting $n$ representative points of the 3D ear model. The more points that are considered, the better the matching results, but also the longer the computation time. For normalisation purposes, a fixed list $L_S = [p_1^S, \ldots, p_n^S]$ of $n$ points is selected using a standard ear model $S$. Ear fitting, i.e., determining the optimal parameters for the shape function, will transform $L_S$ into a list $L_E = [p_1^E, \ldots, p_n^E]$ of $n$ points of the best fitting 3D ear

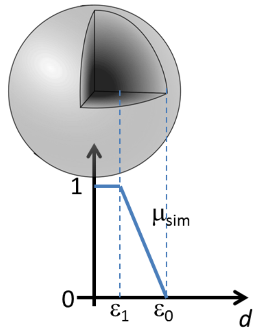


Fig. 2. The similarity function $\mu_{sim}$ and its corresponding sphere.

model $E$. Hereby, each point $p_i^S$ corresponds to the point $p_i^E$ ($i = 1, \ldots, n$). Moreover, using the same standard ear model $S$ and the same list $L_S$ for fitting two different ear models $A$ and $P$ guarantees that each point $p_i^A$ of $L_A$ corresponds to the point $p_i^P$ of $L_P$ ($i = 1, \ldots, n$).

## IV. Ear Recognition

A basic step in ear recognition is the comparison of two left (or two right) ears. As such, in victim identification a set of AM photos of one ear has to be compared with a set of PM photos of the other ear. Using the 3D ear modelling technique explained in the previous section, the feature list $L_A$ of the ear model $A$ of the AM photos has to be compared with the feature list $L_P$ the ear model $P$ of the PM photos.

### *A. Similarity of Corresponding Features*

A commonly used comparison technique for corresponding points of two feature lists is to use the Euclidean distance. In the 3D space defined by the three orthogonal $X$, $Y$ and $Z$-axes, the Euclidean distance between a point $p^A$ of $L_A$ and its corresponding point $p^P$ in $L_P$ is given by:

$$d(p^A, p^P) = \sqrt{(p_x^A - p_x^P)^2 + (p_y^A - p_y^P)^2 + (p_z^A - p_z^P)^2} \tag{7}$$

where $\cdot_x$, $\cdot_y$ and $\cdot_z$ respectively denote the $x$, $y$ and $z$ coordinates of the 3D points.

The similarity between the points is then obtained by applying a similarity function to the respective distances between them. This similarity function $\mu_{sim}$ can generally be defined by a fuzzy set $sim$ over the domain of distances, e.g.,

$$\begin{aligned} \mu_{sim} : [0, +\infty[ &\to [0, 1] \\ d &\mapsto 1, \text{ iff } d \leq \epsilon_1 \\ d &\mapsto 0, \text{ iff } d \geq \epsilon_0 \\ d &\mapsto 1 - \frac{d - \epsilon_1}{\epsilon_0 - \epsilon_1}, \text{ iff } \epsilon_1 < d < \epsilon_0 \end{aligned} \tag{8}$$

where $0 \leq \epsilon_1 \leq \epsilon_0$. Hence, if the distance $d < \epsilon_1$ then the similarity between the points is considered to be 1, if $d > \epsilon_0$, the similarity is 0, and for distances $d$ between $\epsilon_1$ and $\epsilon_0$ the similarity is gradually decreasing from 1 to 0. This is illustrated in Fig. 2.

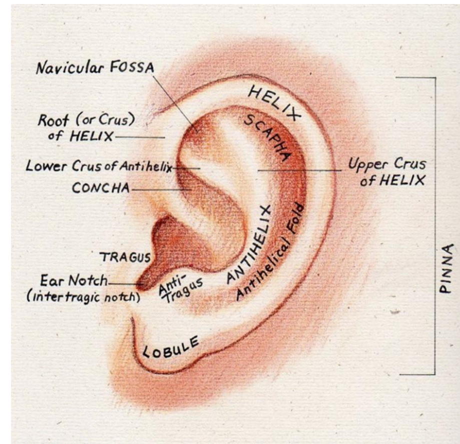


Fig. 3. Different parts of an outer ear.

Hence the similarity between two points $p^A$ and $p^P$ is then obtained by applying

$$\begin{aligned} f_{sim} : \mathbb{P} \times \mathbb{P} &\to [0, 1] \\ (p^A, p^P) &\mapsto \mu_{sim}(d(p^A, p^P)) \end{aligned} \tag{9}$$

where $\mathbb{P}$ denotes the set of all feature points.

### *B. Approaching Similarity Measurement as Criterion Evaluation*

By using Eq. (9), the similarity, or degree of matching, between two points $p^A$ and $p^P$ is expressed by a real number of the unit interval $[0, 1]$ where 0 denotes completely dissimilar, 1 denotes fully similar and increasing numbers reflect an increasing gradation of similarity. Hence, similarity is considered to be a matter of degree (cf. the sphere in Fig. 2).

In what follows, we consider the similarity function $f_{sim}$ to be a criterion specification function. Point distances $d$ that are smaller than $\epsilon_1$ fully satisfy the criterion, whereas distances that are larger than $\epsilon_0$ do not satisfy the criterion at all. Under such an assumption, it becomes possible and quite natural to incorporate multiple criteria evaluation techniques like LSP in the ear matching process. This will be explained in the next subsections.

### *C. Comparing Corresponding Subsets of Features*

Our motivation for including LSP decision making techniques in ear comparison algorithms is the incorporation of forensic knowledge in the matching process. Indeed, forensic experts have considerable knowledge about the typicality of specific shapes of different parts of the outer ear. Fig. 3 contains an overview of the most important distinguished ear parts. Also knowledge about which parts are sensitive to deformations due to glasses, earrings or piercings and information about which parts of the ear are obscured by hair, headgear or other objects might be relevant to fine-tune the ear recognition process.

Hence, we need a facility to group feature points corresponding to an identified part of the ear and compare this group with its corresponding group of feature points for another 3D ear model. By doing so, we will be able to define criteria for feature groups and incorporate these criteria in the ear recognition process.

For that purpose we consider a subset $L_A^S = \{p_1'^A, \ldots, p_k'^A\}$ of the feature list $L_A = [p_1^A, \ldots, p_n^A]$ of the $n$ points of an antemortem ear model $A$, i.e., $L_A^S \subseteq \{p_1^A, \ldots, p_n^A\}$ and its corresponding subset $L_P^S = \{p_1'^P, \ldots, p_k'^P\}$ of the feature list $L_P = [p_1^P, \ldots, p_n^P]$ of the postmortem ear model $P$ involved in the comparison, i.e., $L_P^S \subseteq \{p_1^P, \ldots, p_n^P\}$.

The group similarity (or matching degree) between two (corresponding) subsets $L_A^S$ and $L_P^S$ is then obtained by applying

$$f_{sim}^G : \mathbb{P}^k \times \mathbb{P}^k \to [0, 1] \tag{10}$$
$$(\{p_1'^A, \ldots, p_k'^A\}, \{p_1'^P, \ldots, p_k'^P\}) \mapsto s$$

where $\mathbb{P}^k$ denotes the set of all feature subsets consisting of $k$ points of $\mathbb{P}$ and $s$ is defined by

$$s = \frac{\sum_{i=1}^{k} \mu_{sim}(d(p_i'^A, p_i'^P))}{k}. \tag{11}$$

Hence, the group similarity between two subsets of features is considered to be the average of the similarities of all corresponding features contained in the subsets. Other definitions are possible here. For example, when a pessimistic approach is used, $s$ can be defined as the worst similarity among the similarities of all corresponding features. In that case we have

$$s = \min_{i \in \{1, \ldots, k\}} \mu_{sim}(d(p_i'^A, p_i'^P)). \tag{12}$$

### D. Comparing 3D Ear Models by Applying LSP Aggregation

For the comparison of two 3D ear models $A$ (antemortem) and $P$ (postmortem), a finite set of attributes $\{a_1, \ldots, a_m\}$ is considered. Each attribute represents a specific characteristic of the ear model. Two kinds of attributes are distinguished: attributes that denote a group of feature points and attributes that denote some kind of metadata like, e.g., the age, gender or race of the person, the presence of specific characteristics like birthmarks or tattoos and the presence of objects like glasses, earrings or piercings. Each attribute $a$ has a specific value for both $A$ and $P$, resp. denoted by $a[A]$ and $a[P]$. For a group of feature points this value is the actual subset of feature points extracted from $A$ (resp. $P$). For metadata, this value is, e.g., the actual age, gender or race of the person under consideration.

For each attribute $a$ a corresponding elementary criterion $c$ is defined. For a group attribute this criterion is specified by a group similarity function $f_{sim}^G$ (cf. Eq. 10), which takes the feature subsets of both ear models as arguments and computes the matching degree of those subsets as specified above. In what follows, this matching degree will be called the satisfaction degree of the criterion. For a metadata attribute, the criterion compares actual attributes values for both ear models and also returns a satisfaction degree. For example, a criterion on gender might check whether the gender of the persons of $A$ and $P$ match or not.

Hence, $m$ criteria $c_i$, $i = 1, \ldots, m$ are considered and the evaluation of each criterion returns an elementary satisfaction degree $s_i$, $i = 1, \ldots, m$, which is a real number in the unit interval $[0, 1]$, i.e.,

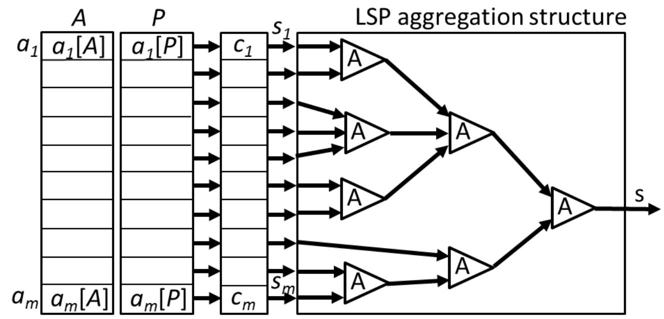


Fig. 4. LSP aggregation structure.

$$c_i : dom_{a_i} \times dom_{a_i} \to [0, 1] \tag{13}$$
$$(a_i[A], a_i[P]) \mapsto s_i = c_i(a_i[A], a_i[P]).$$

where $dom_{a_i}$ is the domain of $a_i$, which is the set of all acceptable values for $a_i$. This is illustrated in Fig. 4.

Next, the elementary satisfaction degrees have to be aggregated to an overall satisfaction degree that expresses the overall degree of matching between $A$ and $P$. For that purpose, an LSP aggregation structure is used [11]. This aggregation structure has to be configured in such a way that it adequately reflects forensic expert decision making strategies. Configuration is done in a hierarchic way by selecting GCD aggregators (cf. Eq. (1)). Each aggregator processes the satisfaction degrees originating from the evaluation of criteria that from the expert's point of view logically belong together. For example, one aggregator can group criteria that check the presence of piercings and earrings. Another aggregator can group criteria that relate to the central parts of the ear (ear notch, tragus, anti tragus and concha).

For each aggregator, two kinds of parameters have to be provided: weights and the orness parameter. A weight $w_i \in [0, 1]$ is assigned with each input $x_i$ of the aggregator. The weights should sum up to one, i.e., if we have an aggregator with $l$ satisfaction degrees as input, $\sum_{i=1}^{l} w_i = 1$. In this way, each weight reflects the relative importance of its input. The orness $\omega \in [0, 1]$ determines the logical behaviour of the aggregator. Orness stands for replaceability, whereas its complement andness stands for simultaneity. So, if we want all inputs to be satisfied we should choose a high simultaneity, which corresponds to a low value for $\omega$. To simplify configuration, a predetermined list of orness values is used [11]. With this list we can choose between disjunction (D), hard partial disjunction (HPD), partial disjunction (PD), soft partial disjunction (SPD), average (A), soft partial conjunction (SPC), partial conjunction (PC), hard partial conjunction (HPC) and conjunction (C).

The compound aggregator CPA (resp. DPA) (cf. Eq. (3), resp. Eq. (4)) can be used to combine a mandatory input $x$ with an optional input $y$ (resp. a sufficient input $x$ with an optional input $y$). In that case a mean penalty percentage $P$ and a mean reward percentage $R$ have to be provided. These percentages can be zero and will be used to adapt the satisfaction of $x$ in case the optional criterion is satisfied (resp. not satisfied).

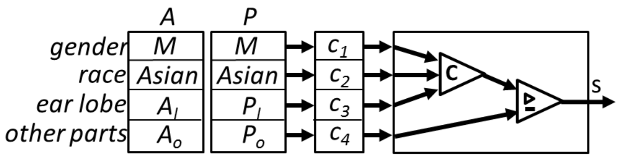


Fig. 5. Illustrative example.

At the end of the aggregation process, a single satisfaction degree $s \in [0, 1]$ is obtained. This satisfaction degree reflects how good $A$ and $P$ match considering the used criteria and aggregation structure.

## V. Illustrative Example

Consider a simplified situation as depicted in Fig. 5. We have an antemortem ear model $A$ and a postmortem ear model $P$. There are four attributes: two metadata attributes *gender* and *race* and two attributes denoting subsets of feature points *ear lobe* and *other parts*. The attribute *ear lobe* contains the subset of the feature points of an ear model that belong to the ear lobe, whereas the attribute *other parts* contains the subset of all other feature points.

For each attribute there is a corresponding criterion. Criteria $c_1$ and $c_2$ respectively check whether the gender and race of $A$ and $P$ match or not. Criterion $c_3$ compares the subsets $A_l$ and $P_l$ of feature points that belong to the ear lobe, whereas criterion $c_4$ compares the subsets $A_o$ and $P_o$ of the remaining feature points. For both comparisons, Eq. (10) is used.

The aggregation structure consists of two aggregators. The first aggregator is a full conjunction operator $C$. It is used to aggregate the satisfaction degrees resulting from the evaluations of $c_1$, $c_2$ and $c_3$. Herewith it is reflected that these criteria are considered to be mandatory, i.e., they should all be satisfied, otherwise the ear models do not match. In this simple case we assume that the three criteria $c_1$, $c_2$ and $c_3$ are of equal importance, which can be modelled by assigning a weight of $1/3$ to each of them. The second aggregator is a conjunctive partial absorption operator $\trianglerighteq$. This operator takes the satisfaction degree resulting from the full conjunction operator as mandatory input. The result of the evaluation of $c_4$ is the optional input. Herewith, it is reflected that the comparison of the ear lobes is optional. If the lobes match, depending on the degree of matching, a maximal reward $R\%$ is assigned to the result of the evaluation of the full conjunction. Else a maximal penalty $P\%$ is assigned (cf. Section II). $R$ and $P$ are provided by the expert and can for example resp. be 20 and 0.

This simple example illustrates the added value of the proposed approach. Thanks to the use of the LSP aggregation structure, complex knowledge, like the fact that the ear lobe bulges out for elderly people so that lobe comparison should not have an significant impact on the ear comparison, can be taken into account in the comparison process.

## VI. Conclusions and Future Work

In this paper, we described some theoretical aspects of a novel approach for comparing 3D ear models. Soft computing techniques based on Logic Scoring of Preference (LSP) aggregation allow to reflect forensic expert knowledge in the ear recognition process more adequately. It is expected that this will lead to better ear identification techniques.

The focus in the paper is on the ear recognition and decision processes of an ear identification approach. The presented technique departs from a 3D ear model that is obtained from ear detection, normalisation and enhancement processes. From each 3D ear model a feature list of points is extracted. The points of a feature list can be subdivided in subsets which can be compared independently. Comparison results are aggregated using an LSP aggregation structure, which can be configured so that it reflects forensic expert knowledge as adequate as possible. Criteria for metadata can be included in the comparison process.

Up to now the approach has only been tested on synthetically modified ear models, hereby using simple aggregation structures (as a proof of concept). A more advanced aggregation structure has to be developed. Experiments with models of real ears are also required for parameter fine-tuning and validation purposes. These two aspects will be subjects for our further research.

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